REMARKS

[0003] Applicant respectfully requests entry of the following remarks and reconsideration of the subject application. Applicant respectfully requests entry of the amendments herein. The remarks and amendments should be entered under 37 CFR. § 1.116 as they place the application in better form for appeal, or for resolution on the merits.

[0004] Applicant respectfully requests reconsideration and allowance of all of the claims of the application. Claims 37-41 and 72-82 are presently pending. Claims amended herein are 37-41, 72 and 78-82. Claims withdrawn or cancelled herein are 1-36 and 42-71. No new claims are added herein.

Statement of Substance of Interview

[0005] The Examiner graciously talked with me—the undersigned representative for the Applicant—on July 17, 2008. Applicant greatly appreciates the Examiner's willingness to talk. Such willingness is invaluable to both of us in our common goal of an expedited prosecution of this patent application.

[0006] During the interview, I discussed how the claims differed from the cited references, namely Warthen, Bowman, Lin and Fung. Without conceding the propriety of the rejections and in the interest of expediting prosecution, I also proposed several possible clarifying amendments.

[0007] I understood the Examiner to tentatively agree that independent independent claim 37 would be patentable over the cited art if amended as

discussed during the interview, but that further review of the references would be required.

[0008] Applicant herein amends the claims in the manner discussed during the interview. Accordingly, Applicant submits that the pending claims are allowable over the cited references of record for at least the reasons discussed during the interview.

Formal Request for an Interview

[0009] If the Examiner's reply to this communication is anything other than allowance of all pending claims, then I formally request an interview with the Examiner. I encourage the Examiner to call me—the undersigned representative for the Applicant—so that we can discuss this matter so as to resolve any outstanding issues quickly and efficiently over the phone.

[0010] Please contact me or my assistant to schedule a date and time for a telephone interview that is most convenient for both of us. While email works great for us, I welcome your call to either of us as well. Our contact information may be found on the last page of this response.

Claim Amendments

[0011] Without conceding the propriety of the rejections herein and in the interest of expediting prosecution, Applicant amends claims 37-41, 72 and 78-82 herein. Applicant amends claims to clarify claimed features. Such amendments are made to expedite prosecution and to more quickly identify allowable subject matter. Such amendments are merely intended to clarify the claimed features, and should not be construed as further limiting the claimed invention in response to the cited references.

Formal Matters

[0012] This section addresses any formal matters (e.g., objections) raised by the Examiner.

Drawings

[0013] The Examiner objects to the drawings under 37 CFR 1.83(a) for not showing all of the features/elements of claims 37, 72 and 78. Applicant respectfully disagrees. At a minimum, figures 1, 2, 3, 4, 6 and 7 show all of the features and elements as recited in claims 37, 72 and 78. Additionally, Applicant respectfully requests the Examiner review at least pages 5-6, 10-11, 14-17 and 19-28 of the Application where features of these claims are discussed with regard to the figures.

[0014] The Examiner objects to Figs. 5 and 8-9 for not being in English as per 37 C.F.R. 1.52(b)(1)(ii) which states:

> (1) The application or proceeding and any amendments or corrections to the application (including any translation submitted pursuant to paragraph (d) of this section) or proceeding, except as provided for in § 1.69 and paragraph (d) of this section, must:
>
> (ii) Be in the English language **or be accompanied by a translation** of the application and a translation of any corrections or amendments into the English language **together with a statement that the translation is accurate.**

[0015] Herewith, Applicant amends the specification to provide the translation as specified in 37 C.F.R. 1.52(b)(1)(ii) and provides a statement that the translation is accurate.

[0016] The Examiner objects to Figs. 8-9 for improper shading. Herewith, Applicant submits replacement drawings to correct the informalities noted by the Examiner.

Claims

[0017] The Examiner objects to claims 38-41 and 78 for minor informalities. Herein, Applicant amends these claims, as shown above, to correct the informalities noted by the Examiner.

Substantive Matters

Claim Rejections under § 112 1ST ¶

[0018] The Examiner rejects claims 37, 72 and 78 under § 112, 1st ¶, as failing to comply with the written description requirement. In particular, the Examiner states that the terms "iterative training" and the "determination of the relevance" are not defined and thereby fail to specify the limitations of the claims. Applicant respectfully traverses this rejection. Based on the claims as amended as well as the discussion below, Applicant contends that these rejections are moot. Accordingly, Applicant asks the Examiner to withdraw these rejections.

[0019] Regarding the Examiner's rejection of the claimed term "iterative training", Applicant contends that the claimed "iterative training of a neural network ... wherein the neural network utilizes a *non-linear activation function*" as recited, for example, in claim 37, is well known to one skilled in the art at the time of the invention. As an example of evidence, Applicant provides an excerpt from the book "Neural Computing Architectures-The Design of Brain-Like Machines", edited by Igor Aleksander, The MIT Press, Cambridge, Massachusetts, 1989, p. 76:

the weight in the interconnection from unit n to unit i, by $\mathbf{b}_{ki}$ the weight in the interconnection from external input k to unit i, and by $\mathbf{c}_i$ the bias term of unit i. The activation levels of the units are then given by:

$$s_i = \sum_{n=1}^{N} \mathbf{a}_{ni} y_n + \sum_{k=1}^{K} \mathbf{b}_{ki} x_k + \mathbf{c}_i \qquad (i = 1, \ldots, N), \tag{1}$$

and the unit outputs by:

$$y_i = S_i(s_i) \qquad (i = 1, \ldots, N), \tag{2}$$

where S_i is the non-linear function in unit i (this function may vary from one unit to another). Sigmoids are the most frequently used functions S_i, in backpropagation experiments. However, any other continuously differentiable functions are also acceptable from a theoretical viewpoint. If we designate by O the set of units that produce the external outputs of the network, these outputs are given by:

$$o_p = y_p. \qquad (p \in O). \tag{3}$$

Given a specific input vector $[x_k]$, the solutions of equations (1–3) are the equilibrium states of the network. A network implemented in analogue hardware would find a solution 'automatically' (assuming that no unstability occurred). In computer simulations, the solution can only be found by iterative techniques, because of the non-linearity of the functions S_i and of the existence of feedback. This, however, does not affect in any way the reasonings that follow.

In feedforward perceptrons, the units can be numbered in such a way that the matrix $[a_{ni}]$ is triangular with a null diagonal, and Equations (1–3) yield the equilibrium state of the network in a straightforward manner. If we denote by d_p the desired values of the outputs for the specific input vector being considered, the output errors are given by

$$e_p = o_p - d_p \qquad (p \in O), \tag{4}$$

and the total squared error for that input vector is

$$E = \sum_{p \in O} e_p{}^2. \tag{5}$$

Backpropagation is a learning rule that corresponds to gradient minimization of the average of E (this average is computed over all input vectors in a specific training set). The essential point of this learning rule is that in feedforward perceptrons the partial derivatives of E relative to the interconnection weights can be computed through a simple backward propagation of the output errors e_p. We will see that this backward propagation procedure can be formulated in terms of simple operations (linearization and transposition) performed on the perceptron network.

[0020] As stated above between equations 3 and 4, "In computer simulations, the solution can ***only*** be found by ***iterative techniques***, because of the ***non-linearity of the functions*** S_i and the existence of feedback".

[0021] As further evidence, Applicant's Specification, pages 27-28 reference S. Russell, P. Norvig (hereafter Russell), "Artificial Intelligence", Prentice-Hall, Inc. 1995, pp 573-577.

[0022] The following excerpt from Russell, p 577, illustrates the generic neural network learning method:

```
function NEURAL-NETWORK-LEARNING(examples) returns network

  network ← a network with randomly assigned weights
  repeat
     for each e in examples do
        O ← NEURAL-NETWORK-OUTPUT(network, e)
        T ← the observed output values from e
        update the weights in network based on e, O, and T
     end
  until all examples correctly predicted or stopping criterion is reached
  return network
```

Figure 19.11 The generic neural network learning method: adjust the weights until predicted output values **O** and true values **T** agree.

perceptrons. It was not until 1969 that Minsky and Papert undertook what should have been the first step: analyzing the class of representable functions. Their book *Perceptrons* (Minsky and Papert, 1969) clearly demonstrated the limits of linearly separable functions.

In retrospect, the perceptron convergence theorem should not have been surprising. The perceptron is doing a **gradient descent** search through weight space (see Chapter 4). It is fairly easy to show that the weight space has no local minima. Provided the learning rate parameter is not so large as to cause "overshooting," the search will converge on the correct weights. In short, perceptron learning is easy because the space of representable functions is simple.

[0023] Figure 19.11 above illustrates the generic neural network learning method of *iterative training* as indicated by the "**repeat** ... **until** all examples correctly predicted or stopping criteria is reached". Additionally, Norvig describes other "iterative training" techniques such as the iterative training of genetic algorithms and the iterative training of neural networks with one or more hidden layers. Applicant contends that based on at least the evidence presented above, that the concept of iterative training is synonymous with technologies utilizing neural networks (and genetic algorithms).

[0024] Regarding the Examiner's rejection of the claimed term "determination of the relevance", as an example, the Application, pages 5-6, state the following (emphasis added):

> The search engine has a log analyzer to evaluate the log database and glean information that improves performance of the search engine *over time*. For instance, *the search engine uses the log data to train the parser and the question matcher*. As part of this *training*, the log analyzer is able to derive various weighting factors indicating how ***relevant*** a question is to a parsed concept returned from the parser, or how ***relevant*** a particular answer is to a particular question. These weighting factors help the search engine obtain results that are more likely to be what the user intended based on the user's query.
>
> In this manner, depending upon the intelligence provided in the query, the search engine's ability to identify relevant answers can be statistically measured in terms of a ***confidence rating***. Generally, the confidence ratings of an accurate and precise search improve with the ability to parse the user query.

[0025] The Application, page 11, states the following (emphasis added):

added):

> The search engine includes a query log analyzer 148 that tracks the query, the returned results, and the user's feedback to those results in a log database. The query log analyzer 148 analyzes the log database to train the FAQ matcher 144. As part of this training, the query log analyzer 148 is able to derive, over time, various weights indicating how ***relevant*** a FAQ is to a parsed concept generated by parsing a particular query, or how ***relevant*** a particular answer is to a particular FAQ. These weights help the search engine obtain results that are more likely to be what the user intended based on the user's query.

[0026] As indicated from the evidence provided, Applicant asserts that the claimed terms "iterative training" and "determination of the relevance" are supported, disclosed and described in the Application. Accordingly, Applicant asks the Examiner to withdraw these rejections.

Claim Rejections under § 101

[0027] Claims 78-82 are rejected under 35 U.S.C. § 101. Applicant respectfully traverses this rejection. Furthermore, in light of the amendments presented herein, Applicant respectfully submits that these claims comply with the patentability requirements of §101 and that the §101 rejections should be withdrawn. Applicant further asserts that these claims are allowable. Accordingly, Applicant asks the Examiner to withdraw these rejections.

[0028] If the Examiner maintains the rejection of these claims, then Applicant requests additional guidance as to what is necessary to overcome the rejection.

Claim Rejections under § 103

[0029] The Examiner rejects claims 37-41 and 72-82 under § 103. For the reasons set forth below, the Examiner has not made a prima facie case showing that the rejected claims are obvious.

[0030] Accordingly, Applicant respectfully requests that the § 103 rejections be withdrawn and the case be passed along to issuance.

[0031] The Examiner's rejections are based upon the following references in combination:

- **Warthen:** *Warthen,* US Patent No. 6,584,464 (issued June 24, 2003);
- **Bowmen:** *Bowmen, et al.,* US Patent No. 6,006,225 (issued December 21, 1999);
- **Lin:** *Lin, et al.,* US Patent No. 6,675,159 (issued January 6, 2004); and
- **Fung:** *Fung, et al.,* US Patent No. 6,687,689 (issued February 3, 2004).

Overview of the Application

[0032] The Application describes a technology for a search engine architecture that is designed to handle a full range of user queries, from complex sentence-based queries to simple keyword searches (Application, Abstract).

Cited References

[0033] The Examiner cites Warthen as the primary reference in the obviousness-based rejections. The Examiner cites Bowmen, Fung and Lin as secondary references in the obviousness-based rejections.

Warthen

[0034] Warthen describes a technology for an information server that directs users to desired sources of information where the desired sources of information are determined, at least in part, based on user input (Warthen, Abstract).

Bowmen

[0035] Bowmen describes a technology for a search engine which suggests related terms to the user to allow the user to refine a search (Bowman, Abstract).

Lin

[0036] Lin describes a technology for a concept-based indexing and search system that indexes collections of documents with ontology-based predicate structures through automated and/or human-assisted methods (Lin, Abstract).

Fung

[0037] Fung describes a technology for a system and associated methods to identify documents relevant to an inputted natural-language user query (*Fung*, Abstract).

Obviousness Rejections

Lack of *Prima Facie* Case of Obviousness (MPEP § 2142)

[0038] Applicant disagrees with the Examiner's obviousness rejections. Arguments presented herein point to various aspects of the record to demonstrate that all of the criteria set forth for making a prima facie case have not been met.

Based upon Warthen, Bowman and Lin

[0039] The Examiner rejects claims 37-41 under 35 U.S.C. § 103(a) as being unpatentable over Warthen, Bowman and Lin. Applicant respectfully traverses the rejection of these claims and asks the Examiner to withdraw the rejection of these claims.

Independent Claim 37

[0040] Applicant submits that the combination of Warthen, Bowman and Lin does not render this claim obvious because it does not teach at least the following features/elements as recited in this claim (with emphasis added):

- analyzing a log database to determine a relevance of previously stored frequently asked questions to the query, the analyzing comprising:
  - *deriving confidence values associated with rules* that indicate how reliably the rules relate the query to the list of frequently asked questions;
  - *deriving confidence values associated with items in the rules* that indicate how reliably the rules are matched to the query;
  - wherein the derivation of at least one of the confidence values associated with items in the rules is facilitated by *iterative training of a neural network* using data from the log database as training data
  - wherein the neural network utilizes a *non-linear activation function*
  - deriving confidence values based on how many words in the query match items in the rule,
  - assigning weights indicating how probable the query pertains to the frequently asked questions; and
  - assigning weights indicating how probable particular answers pertain to particular frequently asked questions,
  - wherein the weights are derived over time based on training facilitated by data in the log database
  - *wherein the confidence values and weights facilitate the determination of the relevance*

[0041] The Examiner indicates (Action, p. 5-8) the following with regard regard to this claim:

Warthen teaches "*mapping the query from a query space to a question space to identify associated frequently asked questions*," see col. 2, lines 1-11, "a semantic network to obtain a weighted list of well-formed questions representative of possible semantic meanings for the initial user query."

Warthen teaches "*mapping the associated frequently asked questions from the question space to a template space to identify associated templates*," see col. 3, lines 41-51, "QPE 30 is coupled to dictionary 34 and semantic net snapshot 40 and uses the information obtained from those sources to generate template questions in response to a user-entered question" where QPE means "Query Processing Engine" and the referenced "semantic net" is the claimed "question space."

Warthen teaches "*mapping the templates from the template space to an answer space to identify associated answers*," see col. 3, lines 41-51, "Template questions are questions that are mapped to answers in question-answer mapping table 42."

Warthen teaches "*and returning the answers in response to the query*," see col. 4, lines 19-24, "information server 50 uses AE [*sic*] to generate answers to the questions and either presents the user with one or more URL's of sites that answer the initial question" where "AE" should be "APE" and means "Answer Processing Engine", see Fig. 1.

Warthen teaches logging previous queries, see col. 4, lines 31-42, "The query is logged to log files 20 for use in further refining information server 50." Warthen does not explicitly teach "*the mapping comprises: analyzing a log database to determine a relevance of previously stored frequently asked questions to the query.*" Bowman does, however, see col. 4, lines 23-43, "the query term correlation date is regenerated periodically from recent query submissions, such as by using the last M days of entries in a query log, and thus heavily reflects the current tastes of users." Thus, it would have been obvious to one of ordinary skill in the database art at the time of the invention to combine the teachings of the cited references because Bowman's teachings would have allowed Warthen's method to gain greater query refinement, see col. 4, lines 23-43.

Warthen does not explicitly teach "*deriving weighting factors based on the iterative training, wherein the weighting factors are used to determine the relevance.*" Bowman does, however, see col. 7, line 60 – col. 8, line 14, "the query term correlation data is preferably generated from the query log 135 using the table generation process... A hybrid approach can alternatively be used in which the table is generated from a large number of log files, but in which the most recent log files are given greater weight." Thus, it would have been obvious to one of ordinary skill in the database art at the time of the invention to combine the teachings of the cited references because Bowman's teachings would have allowed Warthen's method to gain greater query refinement, see col. 4, lines 23-43.

Warthen does not teach "*and ascertaining from the previously stored frequently asked questions the associated frequently asked questions based on the determined relevance.*" Bowman does, however, see col. 4, lines 23-43, "As a result, the related terms suggested by the search engine tend to be terms that correspond to the most frequently searched items during the relevant time period." Thus, it would have been obvious to one of ordinary skill in the database art at the time of the invention to combine the teachings of the cited references because Bowman's teachings would have allowed Warthen's method to gain greater query refinement. see col. 4, lines 23-43.

Warthen and Bowman do not teach "*the analyzing comprises: iteratively training a search engine using data in the log database.*" Lin does, however, see Figs. 7-8 and col. 19, line 60 - col. 20, line 9, "the object is to train the Bayes classifier 130 to learn membership criteria for a specific topic… In this mode, topic editors provide training data in the form of specific documents known to belong to the selected topic or domain," where the process is iterative as shown by the arrows in Fig. 7 and the code loops in Fig. 8. Thus, it would have been obvious to one of ordinary skill in the database art at the time of the invention to combine the teachings of the cited references because Lin's teachings would have allowed Warthen and Bowman's method to gain a method of accurately training the search system, see col. 19, line 60 - col. 20, line 9. Warthen does teach "*wherein the search engine comprises a query parser and a FAQ matcher,*" see Fig. 5 and col. 5, lines 26-35, "Referring now to FIG. 5, a block diagram of QPE 30 and APE 32 is shown with QPE 30 comprising… a parser 155," where the claimed "query parser" is the referenced Parser 155 and the claimed "FAQ matcher" is the referenced APE 32.

Warthen and Bowman do not teach "*identifying a confidence rating which measures a degree of the relevance between the previously stored frequently asked questions and the query.*" Lin does, however, see col. 12, lines 30-42, "The basic premise of relevancy searching is that results are sorted, or ranked according to certain criteria. The system provides a comparison and ranking algorithm, described below, to determine the similarity between a query from a user and a document, and rank each document based upon a set of criteria," where the claimed "confidence rating" is the referenced "ranking." Thus, it would have been obvious to one of ordinary skill in the database art at the time of the invention to combine the teachings of the cited references because Lin's teachings would have allowed Warthen and Bowman's method to gain more relevant results, see col. 12, lines 30-42.

[0042] Applicant agrees with the Examiner that Warthen does not explicitly teach the claimed "mapping comprising: analyzing a log database to determine a relevance of previously stored frequently asked questions to the query" (Action, p. 6).

[0043] However, the Examiner has failed to show that Bowman compensates for this deficiency. The Examiner states that Bowman describes the claimed "mapping comprising: analyzing a log database to determine a relevance", citing Col. 7, line 60 – Col. 8, line 14. However, nowhere in this excerpt does it teach or suggest, for example, the claimed "deriving confidence values associated with *rules ... items in the rules ...* based on how many *words in the query match items in the rules*". Rather, Bowman teaches generating query term correlation data from a query log. The query term correlation dat[a] is regenerated periodically from recent query submissions, such as by using the last M days of entries in a query log, and thus heavily reflects the current tastes of users. As a result, the related terms suggested by the search engine tend to be terms that correspond to the most frequently searched items during the relevant time period (Col. 4, lines 23-27).

[0044] Applicant further agrees with the Examiner that Warthen and Bowman do not teach the claimed "analyzing comprising: iteratively training a search engine using data in the log database" (Action, p. 7).

[0045] However, the Examiner has failed to show that Lin compensates for compensates for this deficiency. The Examiner states that Lin describes the claimed "analyzing comprising: iteratively training a search engine using data in

the log database", citing Figs. 7-8, Col. 19, line 60 – Col. 20, Line 9. However, nowhere in this excerpt does Lin teach or suggest, for example, the claimed "deriving confidence values associated with rules ... items in the rules ... based on how many words in the query match items in the rules". Rather Lin teaches iteratively training a Bayes classifier to learn membership criteria for a specific topic (Col. 19, line 60 – Col. 20, Line 9).

[0046] Furthermore, Lin does not teach "wherein the derivation of at least one of the confidence values associated with items in the rules is facilitated by iterative training of a neural network using data from the log database as training data, wherein the neural network utilizes a non-linear activation function". As stated above, Lin teaches iteratively training a Bayes classifier to learn membership criteria for a specific topic. This is not analogous to the Bayes classifier being trained to learn "**confidence values** associated with **items in the rules**".

[0047] In contrast, Applicant's amended claim 37 recites "analyzing a log log database to determine a relevance of previously stored frequently asked questions to the query, the analyzing comprising: *deriving confidence values associated with rules* that indicate how reliably the rules relate the query to the list of frequently asked questions; *deriving confidence values associated with items in the rules* that indicate how reliably the rules are matched to the query, wherein the derivation of at least one of the confidence values *associated with items in the rules* is facilitated by iterative training of a neural network using data from the log database as training data, wherein the neural network utilizes a non-linear activation function; deriving confidence values based on how many

words in the query match items in the rules; assigning weights indicating how probable the query pertains to the frequently asked questions; and assigning weights indicating how probable particular answers pertain to particular frequently asked questions, wherein the weights are derived over time based on training facilitated by data in the log database, wherein the confidence values and weights facilitate the determination of the relevance".

[0048] To assist the Examiner in appreciating the claimed subject matter, Applicant provides the following illustrative excerpt from Applicant's specification (Application, pages 27-28):

> A confidence value indicating how well this rule is matched is then measured. The measurement may be performed, for example, by using *neural networks.*
>
> One suitable implementation is to use a perceptron to measure the confidence. A perceptron has N input units, each of them representing an item in the rule, and one output unit, which represents the *confidence of the rule matching.* To represent the confidence continually, which is not Boolean, a *Sigmoid function* is used as the activation function for the output unit. For the matched item T_{i_i}, the corresponding input is $I_{i_i} = C_{i_i}$, in which C_{i_i} is the confidence of I_{i_i}; whereas for the non-matched item T_{j_i}, the input is $I_{j_i} = 0$.
>
> The output unit is:
>
> $$c_r = sigmoid(\sum_p w_{rp} I_p)$$

where w_{ip} is the weight from input unit I_p to output unit. A *standard gradient descent method* is used to *train* the perceptron, such as that described in S. Russell, P. Norvig, "Artificial Intelligence", Prentice-Hall, Inc. 1995, pp573-577.

[0049] Accordingly, Warthen, Bowman and Lin, alone or in any combination, do not teach or render obvious all of the elements and features of this claim. Accordingly, Applicant asks the Examiner to withdraw the rejection of this claim.

Based upon Warthen, Fung and Lin

[0050] The Examiner rejects claims 72-82 under 35 U.S.C. § 103(a) as being unpatentable over Warthen, Fung and Lin. Applicant respectfully traverses the rejection of these claims and asks the Examiner to withdraw the rejection of these claims.

Independent Claim 72

[0051] Applicant submits that the combination of Warthen, Fung and Lin does not render this claim obvious because it does not teach at least the following features/elements as recited in this claim (with emphasis added):

- producing one or more output from the individual character strings, the one or more output selected from a group consisting of:
  - a parse tree produced from at least one parsable character string of the search query
  - a partially-parsed fragment produced from one or more partially parsable character strings of the search query
  - at least one keyword generated based at least on one non-parsable character string of the search query
  - wherein for each output that comprises a parse tree or a partially-parsed fragment, a relevance of the output to a list of frequently asked questions (FAQ) is determined, the determination of the relevance comprising:
    - *deriving confidence values associated with rules and with items in the rules* that indicate how reliably the rules are matched to the output
    - wherein the derivation of at least one of the confidence values is facilitated by *using data from the log database as training data*
    - assigning weights indicating how the output, the list of frequently asked questions and answers pertain to each other
    - wherein the confidence values and weights facilitate the determination of the relevance

[0052] For example, the combination of Warthen, Fung and Lin does not not teach or suggest the claimed "deriving confidence values associated with *rules and with items in the rules* that indicate how reliably the rules are matched to the output ... *using data from the log database as training data* ... assigning weights indicating how the output, the list of frequently asked

questions and answers pertain to each other". These references are silent regarding these claimed features.

[0053] Furthermore, Applicant agrees with the Examiner that Warthen and Fung do not explicitly teach determining a relevance of the parse tree and the at least one keyword to a list of frequently asked questions (FAQ) (see Action, p. 11). The Examiner states that Lin describes this feature, citing Col. 12, lines 30-42 which states:

> The next component of the system is the comparison and ranking module 170. The basic premise of relevancy searching is that results are sorted, or ranked according to certain criteria. The system provides a comparison and ranking algorithm, described below, to determine the similarity between a query from a user and a document, and rank each document based upon a set of criteria. Since the concept based search and retrieval system 100 will break down each natural language text into a set of predicates, the documents are represented as a predicate library. A user query is converted to one or more predicates. The ranking and comparison algorithm is designed to rank the similarity between two predicate structures.

[0054] However, the Examiner has failed to show how Lin compensates compensates for this deficiency. Nowhere in this excerpt does Lin teach the claimed "determining a relevance" because Lin does not teach or suggest the claimed "deriving confidence values associated with rules and with items in the rules that indicate how reliably the rules are matched to the output, wherein the derivation of at least one of the confidence values is facilitated by using data from the log database as training data; and assigning weights indicating

how the output, the list of frequently asked questions and answers pertain to each other, wherein the confidence values and weights facilitate the determination of the relevance". Rather, Lin teaches that a comparison algorithm is designed to rank the similarity between two predicate structures. This is not analogous to "deriving confidence values associated with rules and with items in the rules that indicate how reliably the rules are matched to the output" as recited in this claim.

[0055] As shown above, the combination of Warthen, Fung and Lin does not teach or render obvious all of the elements and features of this claim. Accordingly, Applicant asks the Examiner to withdraw the rejection of this claim.

Independent Claim 78

[0056] The Applicant has removed the limitation "wherein at least one of the one or more individual character strings comprises a single character" from this claim. Applicant contends that the removal of this limitation is not material to the patentability of this claim in light of the cited references.

[0057] In addition to other elements and features, claim 78 recites, at at least, elements and features that are similar to those recited in claims 37 and 72. As described above, claims 37 and 72 are both allowable over the cited references. Accordingly, Applicant submits that claim 78 is also allowable

over the cited references for reasons similar to those given above with reference to claims 37 and 72.

Dependent Claims

[0058] In addition to its own merits, each dependent claim is allowable for the same reasons that its base claim is allowable. Applicant requests that the Examiner withdraw the rejection of each dependent claim where its base claim is allowable.

Conclusion

[0059] All pending claims are in condition for allowance. Applicant respectfully requests reconsideration and prompt issuance of the application. If any issues remain that prevent issuance of this application, the **Examiner is urged to contact me before issuing a subsequent Action**. Please call or email me or my assistant at your convenience.

Respectfully Submitted,

Lee & Hayes, PLLC
Representatives for Applicant

E John Fain

Dated: 7-28-08

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